# Postprint: Fresh Food Cold Chain Logistics Service Quality Evaluation Method Based on Improved ER

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## Abstract

To address the issue of highly conflicting information in fresh cold chain logistics service quality evaluation, an improved evidence reasoning (ER) method is employed to process indicator assessment information. First, considering the uncertain nature of experts' indicator assessments for fresh cold chain logistics service providers, the ER method is proposed to handle each provider's indicator assessment information. Second, given the high conflict among experts' assessment information for each provider, a cosine similarity function is utilized to measure the degree of conflict variation, evidence weights are calculated based on inter-evidence consistency, and the assessment information is subsequently revised. Then, the evidence reasoning method is applied again to integrate the revised provider assessment information. Finally, an analysis is presented through the example of an enterprise selecting fresh cold chain logistics service providers, with the results compared against those obtained from alternative methods. The findings indicate that the proposed method can effectively resolve high conflict issues and reduce uncertainty arising from such conflicts.

## Full Text

## Preamble

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### Evaluation Method of Fresh Cold Chain Logistics Service Quality Based on Improved ER

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**Abstract:** To address the problem of highly conflicting evaluation information in fresh cold chain logistics service quality assessment, this paper employs an improved Evidence Reasoning (ER) method to process indicator evaluation information. First, considering the uncertainty characteristics of experts' assessments of fresh cold chain logistics service providers' indicators, the ER method is proposed to process each supplier's indicator evaluation information. Second, given the high degree of conflict among evaluation information from different experts for each supplier, a cosine similarity function is used to measure the degree of conflict variation, evidence consistency is used to calculate evidence weights, and the evaluation information is corrected. Then, the evidence reasoning method is applied to integrate the revised supplier evaluation information. Finally, a case analysis is conducted using an enterprise's selection of fresh cold chain logistics service providers, and the results are compared with those calculated by comparison methods. The results demonstrate that the proposed method can effectively resolve high-conflict problems and reduce uncertainty caused by conflict.

**Keywords:** fresh cold chain logistics; logistics service quality; evidence reasoning; cosine similarity function

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## 0 Introduction

With the rapid development of social economy and continuous improvement of living standards, market demands for both the quality and quantity of fresh food have been increasing. In today's competitive market environment, competitive advantages built solely on products have become increasingly insignificant. Many enterprises have shifted their focus to logistics service quality, hoping to gain competitive advantages by improving it. Consequently, quality evaluation of fresh cold chain logistics service providers has become a critical issue.

Fresh cold chain logistics service quality is primarily assessed by customers and experts, but such evaluation information often exhibits subjective uncertainty. Many scholars have studied this problem of uncertain attribute evaluation. Reference [**?**] proposes an intuitionistic fuzzy set method to handle semantic evaluation information for multi-attribute group decision-making problems with linguistic information as indicator evaluation values and uncertain expert and indicator weight information. Reference [**?**] proposes a decision-making method based on Evidence Reasoning (ER) and VIKOR to address the problem of partial decision information loss caused by experts' lack of confidence and uncertainty in their evaluation information. Reference [**?**] proposes a scheme indicator evaluation method based on rough information kilometers for uncertain attribute evaluation information. Among these methods, the ER approach converts evaluation experts' experiential preferences into a unified recognition framework, offering advantages such as no requirement for prior probabilities and simple reasoning logic, making it an effective method for handling uncertain multi-attribute decision-making problems [?]. It has been widely applied in equipment support resource evaluation [?], online safety assessment of dynamic systems [?], cloud service adaptability evaluation [?], and other fields.

In addition to the problem of uncertain indicator evaluation, fresh cold chain logistics service quality assessment may also suffer from highly conflicting evaluation information. Direct integration of indicator evaluation information using ER can produce fusion results that contradict reality. Currently, most scholars have improved upon Dempster-Shafer theory (D-S) to address highly conflicting information. Reference [?] proposes using Jousselme evidence distance to define evidence consistency and adopts a sequential weighted evidence combination method to handle conflicting evidence fusion. Reference [?] proposes a belief interval simulation distance measure to represent conflict between evidences, calculates evidence body weights based on this distance measure, and fuses evidences through weighted averaging to solve the aggregation problem of conflicting evidence. Reference [?] employs discount coefficients to correct conflicting evidence and proposes an improved conflict evidence combination method based on inconsistency measurement to fuse conflicting information. Reference [?] proposes using Pignistic probability transformation to obtain similarity degrees of various evidences and modifies the Basic Probability Assignment (BPA) functions of each evidence to alleviate conflict between evidences.

These methods focus on improvements to D-S approaches, while current research on ER improvement is relatively limited and mainly falls into two categories. The first category averages conflicting information. For example, Reference [?] proposes incorporating average belief into combination rules by first averaging BPA and then processing information integration. Such methods simply average information, which can alleviate conflict but is not suitable for highly conflicting problems and fails to distinguish between conflicting and non-conflicting information. The second category allocates all conflicting information to the unknown domain or distributes it reasonably between known and unknown domains. For example, Reference [?] proposes allocating conflict coefficients between known and unknown domains at a certain ratio. Although this approach uses conflict coefficients to measure evidence conflict and can solve high-conflict problems, it increases the uncertainty of combined evidence.

To address the limitations of existing ER improvement methods and consider the degree of conflict between evidences, this paper proposes an improved ER method based on cosine similarity for evidence conflict measurement. To improve decision reliability, this paper adopts a group decision-making approach to evaluate the service quality of each fresh cold chain logistics service provider. First, the ER method is used to aggregate indicator evaluation information of candidate fresh cold chain logistics service providers to obtain each expert's evaluation information for each candidate. Second, the cosine similarity of each expert's comprehensive evaluation information for each supplier is calculated to measure the degree of conflict, based on which evidence credibility (i.e., evidence weight) is calculated to correct each supplier's evaluation information. Then, the ER method is applied again to fuse the revised evaluation information from each expert for each supplier, obtaining the comprehensive evaluation belief degrees of candidate suppliers. Finally, utility theory is employed to calculate the average utility degrees of each candidate supplier, and candidate fresh cold chain logistics service providers are ranked according to their average utility degrees. A case study of an enterprise selecting a fresh cold chain logistics service provider with better service quality is presented to verify the effectiveness and feasibility of the proposed method.

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## 1.1 Establishing the Evaluation Index System

Ensuring fresh product quality is the fundamental and primary objective of the fresh cold chain logistics service quality system. Evaluation of fresh cold chain logistics service quality involves numerous indicators that are interrelated and mutually influential, collectively determining the service quality of fresh enterprise cold chain logistics. The evaluation primarily encompasses three aspects: (a) assessment of logistics service capabilities that enterprises should possess; (b) assessment of cold chain logistics service process quality provided by enterprises; and (c) assessment of fresh commodity quality [**?**]. Based on these three aspects and drawing from References [**?**]–[**?**], the index system shown in [Figure 1: see original paper] is established. This evaluation index system comprises the overall indicator layer, sub-indicator layer, and basic indicator layer. The overall indicator layer represents the total effectiveness of fresh cold chain logistics service quality to be evaluated. The sub-indicator layer consists of three components: fresh food quality, cold chain logistics service process quality, and logistics service capability. The basic indicator layer comprises 11 basic indicators including fresh food sensory quality, microbiological indicators, chemical indicators, storage temperature control, timeliness, etc.

The meanings of each evaluation indicator are as follows:

**a) Fresh Food Quality.** Fresh food quality is the indicator of greatest concern to customers, primarily evaluated from three perspectives: sensory quality, microbiological indicators, and chemical indicators. Sensory quality assesses fresh food from the angles of color, odor, and elasticity. Microbiological indicators reflect the quantity of microbial flora on the surface of fresh food. Chemical indicators reflect the amount of preservatives added to fresh food.

**b) Cold Chain Logistics Service Process Quality.** This aspect evaluates the packaging, storage, transportation, and distribution processes of fresh products. Storage temperature control refers to the optimal control temperature set to maintain food freshness, which directly affects product quality. Timeliness reflects the coordination among various departments and stages of fresh cold chain logistics. Food packaging safety refers to whether the packaging methods of fresh cold chain logistics service providers can minimize food damage rates. Traceability refers to the traceability of the entire logistics service process.

**c) Logistics Service Capability.** This refers to the internal systems that customers cannot directly perceive but play a supportive role in service quality. Order information processing reflects how quickly enterprises respond to customer demands. Logistics information processing capability refers to the ability to provide real-time feedback on product logistics status, enabling customers to track package logistics information in real time. Service personnel quality concerns whether staff complete various training programs on time and effectively, ensuring work efficiency. Customer demand information processing assesses whether enterprises meet customers' diverse logistics service requirements.

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## 1.2 Quantitative Information Conversion

The basic indicator layer in the fresh cold chain logistics service quality evaluation system includes both quantitative and qualitative indicators. Quantitative indicators include microbiological indicators, chemical indicators, and storage temperature control, while qualitative indicators include fresh food sensory quality, timeliness, and food packaging safety. Converting these different types of data into a unified framework is a prerequisite for applying the ER algorithm. The main advantage of belief distribution representation is that both precise numerical data and uncertain subjective distribution data can be modeled within the belief distribution structure framework. Yang's rule-based information conversion technology, which relies on decision-makers' knowledge and experience, enables the conversion of quantitative and qualitative data in service quality assessment into a unified belief framework, effectively reducing subjective uncertainty. Through transformation, evaluation information for both quantitative and qualitative indicators can be converted into the same evaluation model. The belief distribution form of the evaluation model can be expressed as:

Assume $e_i$ is a quantitative attribute under scheme $a_l$, and it is assessed as grade $H_n$ $(n = 1, \dots, N)$. The grade standard for quantitative attributes is $S(e_i) = \{(H_n, s_{n,i}), n = 1, \dots, N\}$, where $s_{n,i} < s_{n+1,i}$. $\gamma$ represents the expert-provided grade standard interval for quantitative indicators. If $\gamma$ belongs to interval $[s_{n,i}, s_{n+1,i}]$, the belief function $\beta_{n,i}$ that quantitative indicator $e_i$ is assessed as grade $H_n$ can be derived through conversion formulas (1) and (2).

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## 1.3 Qualitative Information Conversion

Qualitative indicators in the fresh logistics service quality evaluation index system, such as timeliness and food packaging safety, cannot be calculated through quantitative methods. However, experts have comprehensive and accurate knowledge of the system indicators and possess certain authority in the field of fresh cold chain logistics research. Therefore, qualitative indicator assessments and belief functions $\beta_{n,i}$ for assessment grades $H_n$ are generally provided directly by experts based on their experiential knowledge. For example, if an expert assesses a certain qualitative indicator as grade $H_n$ with a confidence probability of 0.7, then $\beta_{n,i} = 0.7$, thereby achieving the conversion of qualitative indicator assessments.

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## 2 Related Theory Introduction

[Figure 1: see original paper] Fresh cold chain logistics service quality assessment index system

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## 2.1 Basic Concepts of ER

Assume the scheme set $A = \{a_1, \dots, a_l, \dots, a_L\}$, where $a_l \in A$. The attribute set is $E = \{e_1, \dots, e_i, \dots, e_I\}$, and the attribute weight set is $w = \{w_1, \dots, w_i, \dots, w_I\}$, where $w_i \in [0, 1]$ corresponds to the weight of attribute $e_i$, satisfying $\sum_{i=1}^{I} w_i = 1$.

Assume there are $N$ assessment grades $H = \{H_1, \dots, H_n, \dots, H_N\}$ for evaluating $e_I$ attributes under a scheme. The belief degree that attribute $e_i$ under scheme $a_l$ is assessed as grade $H_n$ can be expressed as $\beta_{n,i}(a_l)$, satisfying $\sum_{n=1}^{N} \beta_{n,i}(a_l) \leq 1$. The belief framework for assessing attribute $e_i$ under scheme $a_l$ can be represented by $S(e_i(a_l)) = \{(H_n, \beta_{n,i}(a_l)), n = 1, \dots, N\}$, meaning that assessments of scheme attributes are conducted through decision matrix $D = [\beta_{n,i}(a_l)]_{I \times N}$.

**Definition 1** Assume the probability assignment function $m_{n,i}$ represents the degree of support from the $i$-th basic attribute $e_i$ for the generalized attribute $y$ being assessed as grade $H_n$. The remaining probability assignment function $m_{H,i}$ represents the degree of support from the $i$-th basic attribute $e_i$ for the generalized attribute $y$ that has not been assigned to any assessment grade, denoted respectively as: $\bar{m}_{H,i}$ represents the remaining probability function unassigned due to weight; $\tilde{m}_{H,i}$ represents the probability function unassigned due to ignorance, which arises from incomplete assessment.

The probability assignment function $m_{n,\Pi(i)}$ represents the degree of support from the $i$-th attribute in $E_{\Pi(i)}$ for the generalized attribute $y$ being assessed as grade $H_n$. $m_{H,\Pi(i)}$ represents the BPA after integrating all basic attributes in $E_{\Pi(i)}$, expressed by $\bar{m}_{H,\Pi(i)}$ for the remaining probability function after integrating all attributes, and $\tilde{m}_{H,\Pi(i)}$ for the unassigned probability function after integrating all attributes. $K_{\Pi(i+1)}(a_l)$ represents the normalization factor for the assessment information of the $(i+1)$-th attribute under scheme $a_l$. $m_{n,\Pi(i)}$

and $m_{H,\Pi(i)}$ can be obtained by integrating $m_{n,i}$ and $m_{H,i}$ through the following integration formulas (5)–(9) [**?**]:

Where: $m_{n,\Pi(1)} = m_{n,1}$, $m_{H,\Pi(1)} = m_{H,1}$, $m_{H,i} = \bar{m}_{H,i} + \tilde{m}_{H,i}$. $\Pi(i+1)$ indicates the integration of $i+1$ basic attributes.

The belief degrees of each indicator assessment grade can be derived through formulas (10) and (11). Where: $\beta_n(a_l)$ represents the belief degree that scheme $a_l$ is assessed as grade $H_n$ under generalized attribute $y$; $\beta_H(a_l)$ represents the belief degree not assigned to any assessment grade, i.e., the degree of information ignorance.

Assume there are $N$ assessment grades in the unified recognition framework, with corresponding utility values $u_n$, and $H_1 < H_2 < ... < H_N$. Then the maximum, minimum, and average utility values are respectively:

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## 2.2 Cosine Similarity

Cosine similarity, proposed by Wen et al. [**?**, **?**], is used to measure the degree of conflict between evidences using cosine metrics. The smaller the cosine similarity, the greater the conflict; conversely, the larger the cosine similarity, the smaller the conflict.

**Definition 2** Let the BPAs of two independent evidence bodies under a unified recognition framework be $m_1(\cdot)$ and $m_2(\cdot)$, with vector forms represented as $\mathbf{m}_1$ and $\mathbf{m}_2$. The cosine similarity between the two evidences [**?**] is: $c(m_1, m_2) = \frac{\langle \mathbf{m}_1, \mathbf{m}_2 \rangle}{\|\mathbf{m}_1\| \|\mathbf{m}_2\|}$; $\|\mathbf{m}\|$ represents the vector modulus.

Mao Yifan et al. [**?**] argue that cosine similarity can effectively measure the degree between two evidence bodies, proposing that when $c(m_1, m_2) = 0$, the two evidences are completely conflicting; when $c(m_1, m_2) = 1$, the two evidences are completely consistent.

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# 3 Improved ER Method and Decision Process

Let the set of candidate fresh cold chain logistics service providers be $A = \{a_1, \dots, a_l, \dots, a_L\}$, where $a_l \in A$. The evaluation attribute set is $E = \{e_1, \dots, e_i, \dots, e_I\}$, with corresponding attribute weight set $w = \{w_1, \dots, w_n, \dots, w_N\}$, where $w_i \in [0, 1]$ corresponds to the weight of attribute $e_i$, satisfying $\sum_{i=1}^{I} w_i = 1$. Assume there are $H$ assessment grades $H_1, H_2, H_3, \dots, H_N$ for evaluating $e_i$ attributes under a scheme. The belief degree that provider $a_l$'s attribute $e_i$ is assessed as grade $H_n$ can be expressed as $\beta_{n,i}(a_l)$, satisfying $\sum_{n=1}^{N} \beta_{n,i}(a_l) \leq 1$. Then the assessment value of provider $a_l$'s attribute $e_i$ can be represented by $S(e_i(a_l)) = \{(H_n, \beta_{n,i}(a_l)), n = 1, \dots, N\}$.

That is, assessments of scheme attributes are conducted through decision matrix $D = [\beta_{n,i}(a_l)]_{I\times N}$.

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### 3.1 BPA Acquisition

Assume the belief degree that provider $a_l$'s attribute $e_i$ is assessed as grade $H_n$ can be expressed as $\beta_{n,i}(a_l)$. Then its corresponding BPA can be calculated through formulas (16) and (17).

Where: The probability assignment function $m_{n,i}(a_l)$ represents the degree of support from the basic attribute $e_i$ of the $l$-th candidate provider for the generalized attribute $y$ being assessed as grade $H_n$. The remaining probability assignment function $m_{H,i}(a_l)$ represents the degree of support from the basic attribute $e_i$ of the $l$-th candidate provider for the generalized attribute $y that has not been assigned to any assessment grade.

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### 3.2 Evidence Weight Calculation

Let the BPAs of two independent evidence bodies under a unified recognition framework be $m_{n,i}(a_l)$ and $m_{n,i}(a_p)$, with vector forms represented as $\mathbf{m}_i(a_l)$ and $\mathbf{m}_i(a_p)$. The cosine similarity between the two evidences is:

Where: $c(m_l, m_p) = \frac{\sum_{n=1}^{N} m_{n,l}\cdot m_{n,p}}{\sqrt{\sum_{n=1}^{N} m_{n,l}^2}\cdot\sqrt{\sum_{n=1}^{N} m_{n,p}^2}}$. When $c(m_l, m_p)$ approaches 0, it indicates greater conflict between the two evidences; when $c(m_l, m_p)$ approaches 1, it indicates less conflict between the two evidences. For convenience, $c(m_l, m_p)$ is abbreviated as $c_{BPA}(l, p)$. In the evidence system, the degree of support received by candidate provider $l$ is $\sup(m_l) = \sum_{p=1,p\neq l}^{L} c_{BPA}(l, p)$, and the credibility of provider $l$'s evaluation information is:

Clearly, $\mathrm{Crd}(m_l)$ satisfies $\sum_{l=1}^{L} \mathrm{Crd}(m_l) = 1$, meaning $\mathrm{Crd}(m_l)$ can serve as the weight $w_l$ of evidence $m_l$.

The initial evidence is corrected according to evidence weight as follows:

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### 3.3 Improved ER Synthesis Method

To address the problem where fusion results of conflicting information contradict reality, this paper proposes an improved ER method to resolve conflict issues. The method primarily uses cosine similarity to measure the degree of conflict in conflicting information, employs similarity to calculate evidence weights, and corrects evidence based on these weights to achieve the purpose of processing conflicting information. The specific flow of the improved ER synthesis algorithm is shown in [Figure 2: see original paper]. The detailed steps are as follows:

[Figure 2: see original paper] Improved ER evidence synthesis flow chart

**a)** Identify the candidate fresh cold chain logistics service providers participating in the evaluation, the fresh cold chain logistics service quality assessment indicators, and the indicator weights. Identify the evaluation experts participating in the assessment and establish expert weights. Use formulas (1) and (2) to unify the quantitative and qualitative indicator assessment framework and obtain the indicator evaluation information for each fresh cold chain logistics service provider provided by each evaluation expert.

**b)** Use formulas (3) and (4) to calculate the BPA and remaining BPA for each supplier's indicator assessment. Then, fuse each fresh cold chain logistics service provider's indicator evaluation information through formulas (5)–(9), and derive each expert's evaluation grade belief degrees for each fresh cold chain logistics service provider using formulas (10) and (11).

**c)** Based on the evaluation grade belief degrees for each supplier obtained from each evaluation expert in step b), calculate the BPA of each expert's evaluation information for each fresh cold chain logistics service provider using formulas (3) and (4). Then, use the cosine similarity formula (18) to calculate the similarity between evaluation information from various experts for each supplier, employ formula (19) to calculate evidence weights, and use formula (20) to correct the BPA of each expert's evaluation information for each fresh cold chain logistics service provider calculated originally through formulas (3) and (4).

**d)** Apply formulas (5)–(9) again to integrate the revised evaluation information for each fresh cold chain logistics service provider from each expert, obtaining the comprehensive evaluation information for each fresh cold chain logistics service provider. Use formulas (10) and (11) again to calculate the comprehensive evaluation grade belief degrees for each fresh cold chain logistics service provider.

**e)** Establish utility values for each assessment grade, use formulas (12)–(14) to calculate the maximum, minimum, and average utility values for each fresh cold chain logistics service provider, and rank the candidate fresh cold chain logistics service providers according to their average utility values.

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## 4 Case Analysis

A fresh food enterprise, aiming to expand its scale and enhance market competitiveness, plans to develop new cold chain logistics business. Five fresh cold chain logistics service providers have bid for the project, and the enterprise intends to comprehensively evaluate their logistics service quality to select a provider with better overall assessment for cooperation. Five evaluation experts $(k_1, k_2, \dots, k_5)$

were invited to participate in this logistics service quality evaluation activity. The five experts evaluated 11 logistics service quality indicators $(e_1, e_2, \dots, e_{11})$ for five fresh cold chain logistics service providers $(Q_1, Q_2, \dots, Q_5)$. All expert weights were set at 0.2, and the 11 indicator weights were 0.09, 0.1, 0.1, 0.09, 0.08, 0.084, 0.09, 0.09, 0.096, 0.09, and 0.09 respectively, with specific indicators shown in Figure 1. The enterprise established three assessment grades $H_1$, $H_2$, and $H_3$, representing Poor, Average, and Good (P, A, G), with corresponding grade utility values of 0.31, 0.33, and 0.36. This evaluation adopted a three-grade format to assess 11 indicators of five fresh cold chain logistics service providers. The quantitative indicator evaluation information provided by expert $k_1$ was converted using formulas (1) and (2) according to the reference standard values for each grade. The resulting logistics service quality evaluation information from expert $k_1$ for the five fresh cold chain logistics service providers is shown in .

Evaluation expert $k_1$'s service quality assessment information for 5 fresh cold chain logistics service providers

After the evaluation experts provided their assessment information, the BPA and remaining BPA for each fresh cold chain logistics service provider's evaluation indicators were calculated using formulas (3) and (4). Then, the indicator assessment information for each supplier provided by each evaluation expert was aggregated sequentially using formulas (5)–(9), and the comprehensive evaluation belief degrees of each expert for each supplier were calculated using formulas (10) and (11), as shown in .

Comprehensive trustworthiness of each expert's evaluation information for each supplier

After obtaining the comprehensive evaluation belief degrees of each expert for each supplier through the ER integration method, the BPA for each supplier's evaluation was calculated using formulas (3) and (4). Then, the similarity between each expert's evaluation information for each supplier and the evidence weights were calculated using the cosine similarity formulas (18) and (19). Finally, the BPA of each expert's evaluation information for each fresh cold chain logistics service provider, originally calculated through formulas (3) and (4), was corrected using formula (20). The revised BPA of each expert's evaluation information for each supplier is shown in .

Revised BPA for each supplier to evaluate information for each supplier

The revised BPA of each expert's evaluation information for each supplier was integrated again using the ER integration formulas (5)–(9), and the comprehensive evaluation belief degrees for each supplier were calculated using formulas (10) and (11). The utility functions (12)–(14) were used to calculate the average utility values for each supplier, with specific values shown in . The suppliers were ranked according to their average utility values, yielding the ranking result: $Q_4 > Q_2 > Q_5 > Q_1 > Q_3$. Based on the ranking results, the fourth supplier demonstrates better cold chain logistics service quality and can be considered the optimal choice.

Average utility value obtained by method and comparison method

To verify the effectiveness of the proposed method, a method that reasonably distributes conflict between known and unknown domains was used to analyze and rank the case in this paper. The average utility values obtained from this analysis are shown in , with a ranking result of $Q_4 > Q_5 > Q_2 > Q_1 > Q_3$. The ranking results show that both methods identify the fourth fresh cold chain logistics service provider as the best cooperative supplier, though there are slight differences in the ranking order. This paper analyzes the reasons for these differences.

The analysis reveals that the uncertain belief degrees obtained by the two methods differ significantly. [Figure 3: see original paper] compares the uncertain belief degrees obtained by the proposed method and the method that distributes conflict between known and unknown domains. The figure shows a significant gap in the comprehensive uncertain belief degrees calculated by the two methods. The main reason for the difference in ranking results is that the method distributing conflict between known and unknown domains fails to consider the uncertainty already present when experts provide evaluation information. Redistributing conflict between known and unknown domains during fusion further increases the uncertainty of evaluation results. In contrast, this paper proposes using cosine similarity to measure conflict between evidences, calculating evidence weights based on similarity to correct evidence, which effectively resolves conflict between evidences and reduces uncertainty in conflicting information fusion.

[Figure 3: see original paper] Comparison of uncertainty between method and comparison method

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## 5 Conclusion

Considering the uncertain nature of indicator evaluation in fresh cold chain logistics service quality, this paper employs traditional evidence reasoning methods to obtain indicator evaluation information. To improve decision reliability, a group decision-making approach is adopted to evaluate the service quality indicators of fresh cold chain logistics service providers. Recognizing that evaluation information may be highly conflicting during the assessment process, this paper proposes an improvement to the traditional ER method. After integrating each supplier's evaluation indicators, the comprehensive evaluation results of each expert for each supplier are obtained. On this basis, the cosine function is used to calculate the degree of conflict among each expert's comprehensive evaluation information for each supplier, and each expert's evaluation information for each supplier is corrected accordingly. The ER method is then applied again to integrate each expert's evaluation information for each supplier, yielding the comprehensive evaluation results for each supplier. To verify the effectiveness and feasibility of the proposed method, a method that reasonably distributes conflict between known and unknown domains was used for comparative analysis. The results show that while both methods yield consistent results, the proposed method can effectively reduce the uncertainty after conflicting information is corrected and fused.

This paper proposes an improved ER method to solve the problems of uncertain indicator evaluation information fusion and conflict. Future research will explore methods for handling conflict issues from the perspective of internal expert conflicts, continuously developing approaches to resolve conflicts that arise during decision-making processes.

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## References

[11] Li Bo. Synthesis assessment method based on Pignistic similarity and improved DS evidence theory [J]. Application Research of Computers, 2018, 35 (12): 3682-3688.

[12] Murphy C K. Combining belief functions when evidence conflicts [M]. [S.l.]: Elsevier Science Publishers B. V. 2000.

[1] Ma Wanyuan, Geng Xiuli. Intuitionistic VIKOR method considering incomplete weights [J]. Application Research of Computers, 2018, 35 (4): 1066-1071.

[13] He Jinfeng, Xu Jichao, Wu Weidong. Improvement of evidential reasoning approach for multiple attribute decision making under uncertainty [J]. Control and Decision, 2006, 21 (4): 385-390.

[2] Wu Lianggang, Wen Li. 2-dimension linguistic multi-criteria group decision making method based on evidence reasoning and VIKOR [J]. Application Research of Computers, 2016, 33 (6): 1697-1702.

[14] Yang Jianbao, Xu Dongling. On the evidential reasoning algorithm for multiple attribute decision analysis under uncertainty [J]. IEEE Trans on, Systems Man & Cybernetics Part A Systems & Humans, 2002, 32 (3): 289-304.

[3] Geng Xiuli, Dong Xueqi. Concept evaluation approach based on rough information axiom and cloud model [J]. computer integrated manufacturing systems, 2017, 23 (3): 661-669.

[15] Wen Chenglin, Wang Yingchang, Xu Xiaobin. Fuzzy information fusion algorithm of fault diagnosis based on similarity measure of evidence [C]//Proc of International Symposium on Neural Networks. Berlin: Springer-Verlag, 2008: 506-515.

[4] Yao Runming, Yang Yulan, Li Baizhan. A holistic method to assess building energy efficiency combining D-S theory and the evidential reasoning approach

[J]. Energy Policy, 2012, 45 (11): 277-285.

[16] Xiao Fuyuan. An improved method for combining conflicting evidences based on the similarity measure and belief function entropy [J]. International Journal of Fuzzy Systems, 2017, 20 (1): 1-11.

[5] Zhou Zhijie, Liu Taoyuan, Li Fangzhi, et al. An evaluation method of equipment support resources based on evidential reasoning [J]. Control and Decision, 2018, 33 (6): 1048-1054.

[17] Mao Yifan, Zhang Duolin, Wang Lu. Directional evidence conflict measurement based on improved cosine similarity [J]. Systems Engineering and Electronics, 2016, 38 (11): 2567-2571.

[6] Zhao Fujun, Zhou Zhijie, Hu Changhua, et al. Online safety assessment method based on evidential reasoning for dynamic systems [J]. Acta Automatica Sinica, 2017, 43 (11): 1950-1961.

[18] Chen Hongli, Lu Hua. study on the process quality evaluation of cold-chain logistics service [J]. China Business and Market, 2013, 27 (1): 34-39.

[7] Fu Chao, Gui Pengfei. Adaption assessment for cloud computing service based on evidence theory [J]. Application Research of Computers, 2012, 29 (11): 4304-4308.

[19] Hsiao Y H, Chen Muchen, Chin C L. Distribution planning for perishable foods in cold chains with quality concerns: Formulation and solution procedure [J]. Trends in Food Science & Technology, 2017, 61: 1-13.

[8] Han Deqiang, Han Chongzhao, Deng Yong, et al. Weighted combination of conflicting evidence based on evidence variance [J]. Acta Electronicasinica, 2011, 39 (s1): 153-157.

[20] Yang Xiaofang, Yao Yu, Fu Qiang. Multi-objective optimization model of cold chain logistics distribution based on freshness [J]. Application Research of Computers, 2016, 33 (4): 1050-1053.

[9] Li Jie, Wang Wei, Gao Xiaoli, et al. Strong conflicting evidences fusion based on belief interval distance measurement [J]. Cluster Computing, 2018: 1-10.

[21] Gulc A. Models and methods of measuring the quality of logistic service [J]. Procedia Engineering, 2017, 182: 255-264.

[10] Zhao Yuxin, Jia Renfeng, Shi Peng. A novel combination method for conflicting evidence based on inconsistent measurements [S.l.]: Elsevier Science Inc, 2016: 125-142.

[22] Rezaei J, Roekel W S. V, Tavasszy L. Measuring the relative importance of the logistics performance index indicators using Best Worst Method [J]. Transport Policy, 2018, 68: 158-169.

*Note: Figure translations are in progress. See original paper for figures.*